Analysis of Pure Weather Portfolios Using Parametric, Non-Parametric, and Conditional VaR in Relation to Bank's Risk Capital

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Abstract

Weather data plays an imperative role in deciding the future prices of commodities and utilities, mainly energy prices. The studies measuring portfolio performances using financial data have mainly dominated the financial literature. The present paper is a different attempt to estimate the portfolio risks (portfolio VaR) for three of the city-wise, that is, Delhi, Mumbai, and Chennai monthly temperature data. Besides this, the portfolio risk capital was measured using point backtest method, thereby using traffic signal violations approach. To generate valuable results, it was important to use not just the historical values, but also randomly generated values for 191 monthly temperature figures. Along with this, conditional VaR accepting the maximum possible losses was also accommodated in the study. The use of GARCH 1, 1 model was attempted, which appears to be able to cover volatility clustering easily. The pure temperature portfolio risks and portfolio risk capital are accounted at different confidence intervals and this is the only scenario utilized for the analysis. With this extensive back-end analysis, the spreadsheet was utilized. This present paper is limited to the usage of temperature data of three cities (Delhi, Mumbai, and Chennai). For future research purposes, a greater number of cities and more weather parameters can be utilized. The banking sector, particularly financing to agricultural based projects, can make much use of such studies not only to safeguard itself against their investment portfolio, but can also use the findings from the present study (if permitted) to manage their capital adequacy requirements for mark-to-market trading portfolios. The results revealed the inter-city comparison of portfolio and individual VaR based risk capital estimations and also provide a model for researchers and practitioners to implement for further use.

Keywords: GARCH model, traffic signal violations (TSV), VaR horizons, back testing, conditional value at risk

JEL Classification : C530, G110,G170, Q510

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According to Tarasov (2011), VaR is the best approach in estimating the downside risks, and this is equally useful from the agricultural industry point of view. The present paper uses portfolio management and tailed VaR to make a city-wise comparison of temperature performances. This study is one of its kind because emphasizing cities' temperature and performing GARCH 1, 1 modeling on tailed conditions is by itself not found in empirical studies conducted in the Indian context. The differences in the portfolio VaR measures and portfolio risk capital as measured using traffic signal violations on temperature variables provide useful strategic understanding to the Indian stock market traders by shifting emphasis from traditional stock only set of trading assets into weather related contracts. Another reason to use temperature variables is because most (nearly 90%) of the existing weather related contracts (derivative contracts) worldwide are for utilities, and these mainly require temperature as a measure for calculating risks.

Review of Literature

Taylor and Buizza (2006) used an ensemble prediction model by using scenarios placed with probability density function. The resultant mean was considered as a fair price of weather derivative and distribution around mean as

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risk for further use in VaR analysis. This paper explained the use of value at risk on the density forecasts obtained by a set of scenarios and taking mean of this as a payoff function. While using atmospheric modeling, instead of simulation, a horizon based probability "bounds" are analyzed which means what are the maximum fluctuations in the weather variables which can lead to an immediate energy demand-supply mismatch. According to one of the research work of Vedenov and Barnett (2004), weather derivatives are typically in the form of index based contracts, and such weather indexes greatly reduce the transaction costs in comparison to the traditional crop yield insurance. However, in the paper, it was revealed that since certain weather phenomena like rainfall is highly localized; this confirms the need for an index to be prepared from the same location and time. Furthermore, the paper also examined VaR based efficiency on crop yield based on derivative contracts and without contracts. A similar tool called mean root square loss (MRSL) was also employed in the study.

Feng (n.d.) stressed heavily on the use of the bootstrap model to estimate weather based portfolio VaR. However, the bootstrap model requires numerous randomly generated simulations, but still, the results appeared similar to normal distribution. Taylor and Buizza (2006) used the put option strategy of the temperature variable for taking decisions. Although prediction models are available, which can statistically predict the temperature of a particular geographical place from a few days to a few months, but long term forecasts, as the paper said, can be effectively predicted by using the time-series modeling framework.

Campbell and Diebold (2005) used the autoregressive forecast model and compared it with the Earthsat Model and it was observed that, with an increase in horizon from 1 to 8, the point forecast results started getting closer to long-term density forecasts as provided by the Earthsat Model. Allen, Kramadibrata, Powell, and Singh (2012) utilized mean-variance and mean-CVaR portfolio optimization techniques on mining stocks during high volatility and low volatility periods. There were some interesting facts which came about like that CVaR and variances effect differently under high-volatility and low volatility periods.

Pasquier (2010) explained the merits of VaR and back testing at specific time horizons for knowing the performance of VaR based risks and reasons for outliers (VaR breaches) and its meaning from the investment management point of view. Tarasov (2011) justified temperature variability to be closely associated with global warming on the one side and improvement in technology to produce superior drought resistant crops on the other side. Such contrasting scenarios make volatility of weather related phenomenon very dynamic, and thus, the GARCH models seem relevant to occupy such changes. According to the Tarasov, tailed VaR is a better mmeasure of catastrophic risks arising out of drought, flood, and so forth. Hence, for such extreme events, the use of coherent risk measure appears to be the best option.

Objective of the Study

The present study is particularly aimed at understanding horizon-based portfolio risk capital estimation using temperature series. This will enable the financial market players to gauge the available risk in a portfolio with pure temperature based series and opportunities for hedging and trading accordingly.

Theoretical Framework

The broad conceptual part of this study encompasses the use of tailed or conditional based model for the temperature values of three cities of Delhi, Mumbai, and Chennai respectively. The aim of using the VaR based model for a platform of diversification is based on the fact that the temperature in these three geographies is very different throughout the year, and usually, with the use of normalized, historical, and tailed approaches, the research seemingly explains the best portfolio risk estimation for a given time frame and the portfolio capital invested.

Methodology

For the present research, careful selection of Delhi, Mumbai, and Chennai temperature figures was made from

1996 to 2012 on a monthly basis. Furthermore, to apply the value-at-risk model, the following three approaches were utilized:

➲ **Non-parametric VaR:** Uses historical temperature values and uses the same to generate individual and pair-wise portfolio VaRs for each of the three temperature combinations - Delhi-Chennai, Mumbai-Chennai, and Delhi-Mumbai respectively.

$$\text{VaR}_{\text{Monthly-Non Parametric}} = \quad _x \quad Z \quad _x\sqrt{n})P \qquad (1)$$

➲ **Parametric VaR:** Is randomized series in replacement of historical values and using the same to generate individual and pair-wise portfolio VaRs for each of the three temperature combinations - Delhi-Chennai, Mumbai-Chennai, and Delhi-Mumbai respectively.

$$\text{VaR}_{\text{Monthly-Parametric}} = \quad _x \quad Z \quad _x\sqrt{n})\,P \qquad (2)$$

➲ **Tailed VaR:** Considering the maximum downside risk out of the non-parametric and parametric, whichever appeared maximum on the time series basis was selected for further calculation. This was further used for pair-wise portfolio VaRs for each of the three temperature combinations, that is, Delhi-Chennai, Mumbai-Chennai, and Delhi-Mumbai respectively.

The formula employed was :

Tailed VaR: = Min (non-parametric VaR monthly, Parametric VaR monthly).

$$\text{VaR}_{\text{Monthly-Tailed}} = MIN(\text{VaR}_{\text{Monthly-Non Parametric}}, \text{VaR}_{\text{Monthly-Parametric}}) \qquad (3)$$

For portfolio VaR, a formula used was as follows:

➲ **Portfolio Risk :**

Here,

Portfolio variance is calculated as: $^{2}_{xy} \quad ^{2}_{x}w^{2}_{x} \quad ^{2}_{y}w^{2}_{y} \quad 2w_x w_y COV_{xy}$ (4)

$$PVaR_{NON\ PARAMETRIC} \quad (\ _x w_x \quad _y w_y \quad Z \quad _{xy}\sqrt{n})\,P \qquad (5)$$

$$PVaR_{PARAMETRIC} \quad (\ _x w_x \quad _y w_y \quad Z \quad _{xy}\sqrt{n})\,P \qquad (6)$$

$$PVaR_{TAILED} = MIN(PVaR_{NON\ PARAMETRIC}, PVaR_{NON\ PARAMETRIC}) \qquad (7)$$

The same formulas were used for the three combinations of Mumbai, Chennai, and Delhi.

The time series modeling was done using GARCH 1, 1 model, where the estimate of α and β were based on the maximum likelihood function. For this, each historical data value was converted into lagged return and lagged variance and then, the maximum likelihood function was applied on the historical series to generate the constant which was used with the formula to generate the GARCH based standard deviations and covariances.

Standard deviation at *n*th variable:

$$^{2}_{x}n \qquad ^{2}_{x\ n\ 1} \qquad ^{2}_{n\ 1} \qquad (8)$$

long term weight, v = long term volatility, considering both to be zero.

Similarly, for covariance between the set of two temperature variables, the formula used was:

Covariance Temp var 1 and 2 at *n*th variable:

$$Cov_{xy} \qquad Cov_{xy_{n\ 1}} \qquad {}_{n\ 1}\ {}_{n\ 1} \tag{9}$$

For generating and , the maximum likelihood function was used, where $_{2}$

$$MLF \quad \log\ ^{2} \quad \text{—} \quad (\text{where},\ ,\ ,\ 0, non \quad negative) \tag{10}$$

Once the temperature VaR and portfolio VaR are generated based on three combinations for non-parametric, parametric, and conditional basis, the next step was to calculate the average portfolio VaR, which was calculated by taking the average of 191 months portfolio VaR. The same is exhibited in the charts and tables, which are primarily used for further analysis.

Another significant feature of the portfolio model was to gather portfolio risk capital based on three pair-wise temperature portfolios. For this, two methods were employed. Point backtest, where the limits for 191 months based at different time intervals were generated. The details of each limit are explained below. These limits were used to test the VaR breaches and acceptances on one side and confirmation of non-normality condition on the other side.

The formula for the point backtest is:

$$\text{Say for 99\% C.I.} = np \quad 2.58 \quad \sqrt{np \quad np^{2}}, np \quad 2.58 \quad \sqrt{np \quad np^{2}}, \tag{11}$$

Similarly for 98%, 95%, and 90%, the ranges are calculated as follows:

(1) For 90% confidence level, the lower limit is 12, and the maximum limit of breaches is 26.
(2) For 95% confidence level, the lower limit is 4, and the maximum limit of breaches is 16.
(3) For 98% confidence level, the lower limit is 0, and the maximum limit of breaches is 8.
(4) For 99% confidence level, the lower limit is 0, and the maximum limit of breaches is 5.

➲ Use of Traffic Signal Violations

To estimate the risk capital based on Point backtest values, the following formula is employed:
Risk capital = min (VaR 191th month, *S* (Factor of 3, 3+ (5- *x*) *0.2 or 4) multiplied by Average of 191 month VaR values)

➲ Individual Risk Capital

$$I_{RC\ \text{Parametric}} \quad \text{MIN}\ [\text{VaR}_{191\text{th}\ \ \text{Parametric}}, (S \quad \text{MeanVaR}_{191\text{month}\ \ \text{Parametric}})] \tag{12}$$

$$I_{RC\ \text{Non-Parametric}} \quad \text{MIN}\ [\text{VaR}_{191\text{th}\ \ \text{Non-Parametric}}, (S \quad \text{MeanVaR}_{191\text{month}\ \text{Non-Parametric}})] \tag{13}$$

$$I_{RC\ \text{Tailed}} \quad \text{MIN}\ [I_{RC\ \ \text{Parametric}}, I_{RC\ \text{Non-Parametric}}] \tag{14}$$

➲ Portfolio Risk Capital

$$P_{RC\ \text{Parametric}} \quad \text{MIN}\ [\text{PVaR}_{191\text{th}\ \text{Parametric}}, (S \quad \text{MeanPVaR}_{191\text{month}\ \text{Parametric}})] \tag{15}$$

$$P_{RC\ \text{Non-Parametric}} \quad \text{MIN}\ [\text{PVaR}_{191\text{th}\ \text{Non-Parametric}}, (S \quad \text{MeanPVaR}_{191\text{month}\ \ \text{Non-Parametric}})] \tag{16}$$

$$P_{RC\ \text{Tailed}} \quad \text{MIN}\ [P_{RC\ \ \text{Parametric}}, P_{RC\ \ \text{Non-Parametric}}] \tag{17}$$

Thus, for the 191 months horizon, the individual VaR risk capital and portfolio risk capital estimates were calculated and are used further in the study. Portfolio risk capital was calculated for all three VaR values, that is, parametric, non-parametric, and tailed basis. The results of the portfolio risk and portfolio risk capital are now analyzed. Dirty back testing was employed here, which means that the weights of the portfolio are assumed to be unchanged throughout the 191 months period.

Figure 1. Monthly 90% 1-month Portfolio Value-at-Risk for Mumbai-Chennai, Delhi Chennai, and Delhi-Mumbai Temperature Combinations

(1996-97 to 2011-2012 (Fig in Rupees)

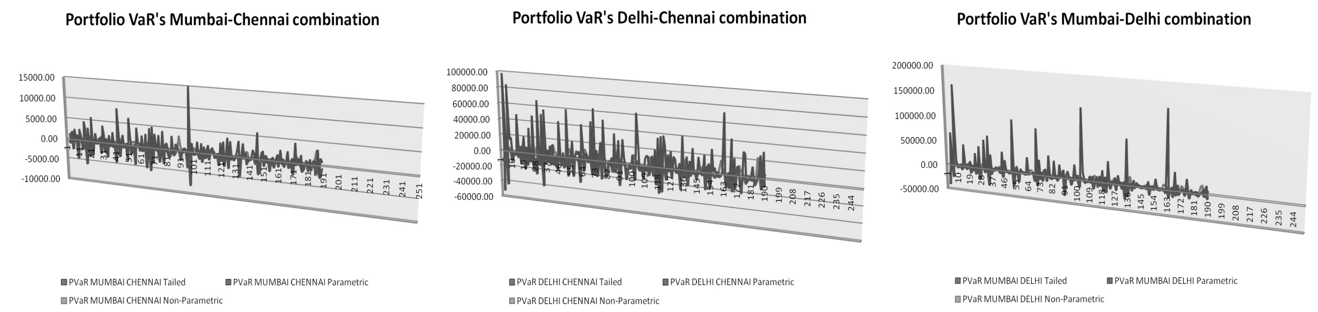
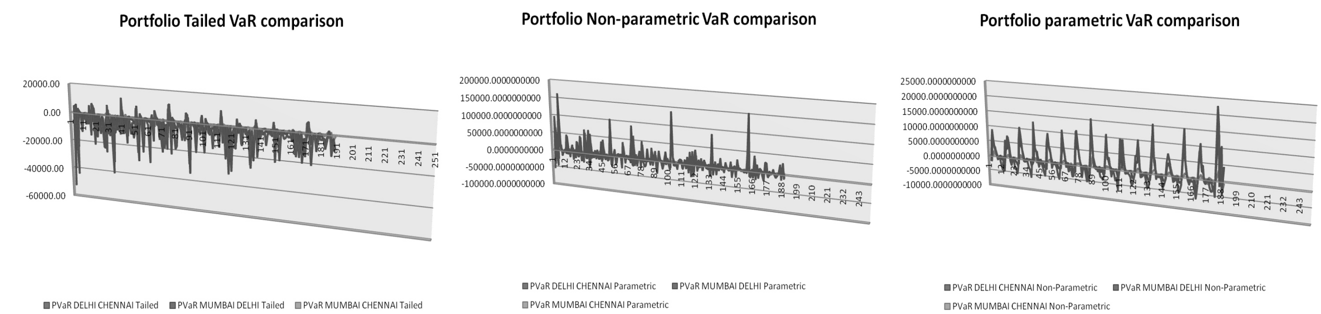


Figure 2. Monthly 90% 1-month Portfolio Value-at-Risk for Mumbai-Chennai, Delhi Chennai, and Delhi-Mumbai Temperature Combinations

(1996-97 to 2011-2012 (Fig in Rupees)



Analysis and Results

After calculating the portfolio VaR by multiplying portfolio standard deviations with the dirty weights of each of the two sets of temperature trading variable, the following portfolio VaRs were obtained. The time-series are displayed and explained in the Figure 1.It can be inferred from the Figure 1 that the three combinations fully reflect the reason of choosing a tailed portfolio VaR combination. In all three combinations, as can be seen, the downside risk is fully covered by the tailed component. Mumbai-Chennai seems better as the range of minimum loss is visibly small as compared to that appearing in Delhi and Chennai temperature combinations. While, for Delhi-Chennai and Mumbai-Delhi, it ranged between ₹ 0-50000, the same is usually under ₹ 0 to -10000 in case of the Mumbai-Chennai combination. In Mumbai - Chennai combination, only once during the 97th-98th month did the value of VaR drop once and hovered around the figure of ₹ - 5000.

As compared to the previous results in Figure 1, by seeing the Figure 2, starting from left for all the tailed combinations, the patterns of portfolio VaR are significantly different from non-parametric and parametric portfolio VaRs. In all the three combinations, Mumbai - Chennai is not visible, that is, the risks are comparatively lower in comparison to the two combinations occupying Delhi; which chiefly relates to the fact that the volatility in Delhi temperatures was found to be more in comparison to the other two cities. Also, from the diversification point of view, Delhi was more sound compared to the other combinations. In case of parametric portfolio, VaR downside volatilities are less as compared to the upside volatilities. What this means is that the GARCH model had been able to capture upside volatility clustering more often than downside volatility clustering. The same, however, is not revealed in either of the two combinations.

It can be inferred from the Table 1, that starting from the Delhi- Chennai combination, from 90% to 99%, the change on average non-parametric VaR was ₹ 1397 per month, this was more than two times in case of parametric

VaR. However, both parametric and non-parametric VaR failed to account for downside risk on an average value basis. Contrary to this, tailed VaR in case of Delhi-Chennai revealed far appealing figures. It can be seen that the coherency of VaR increased an increase in confidence intervals. The average portfolio tailed VaR stood at negative ₹ 8106.

For Mumbai-Delhi, the figures on the non-parametric VaR front were a little down, starting at 90% at ₹ 1289 per month. However, volatility seems maximum with the parametric value as it averaged at a whooping ₹12292 per month, while for the tailed VaR too, it stood at negative ₹ 4881 respectively. Contrary to the above-mentioned two temperature portfolios, Mumbai-Chennai remained more conservative, and upside and downside risks remained relatively very low. Average portfolio VaR for non-parametric case was as low as ₹ 98, while for parametric VaR, it was ₹ 195. Not only this, tailed VaR too was closed at as low as negative ₹1084 per month. This figure of tailed portfolio VaR is significantly lower than negative ₹ 8106 of Delhi-Chennai, and negative ₹ 12292 of Mumbai - Delhi combinations.

Hence, from the hedging point of view, Mumbai-Chennai portfolio seems a better proposition, but for high risk high return perspective, Delhi based combinations can be picked up. Continuing with the explanation of portfolio VaRs of Table 1, let us now focus on how much amount of risk capital one has to account for while considering the portfolios of three temperature variables.

It can be inferred from the Table 2 that the negative portfolio capital is more of a concern on an average, while for Delhi- Chennai, a parametric portfolio risk capital improved from - ₹ 13212 to - ₹ 20785, it averaged at - ₹ 17719 or approximately 17 % of the initial mark-to-market value. This is comparatively very low when it comes to the tailed component that stood at - ₹ 32366, roughly 32% on a monthly basis. However, for Mumbai Delhi, the value peaked at ₹19396 a month. As usual, just like portfolio VaR, the figures of risk capital were also too low in case of the Mumbai - Chennai combination, it averaged at just ₹ 4390.25 a month.

Research Implications

The paper provides a research impetus on the use of temperature data across cities for better hedging and portfolio management. This paper also covers the empirical dimension of exploring the BASEL norms of risk capital

Table 1. Average Portfolio Value-at-risk Measures with Generalized Autoregressive Heteroskedasticity Model (GARCH 1,1)

(1996-97 to 2011-2012)

Portfolio VaR using GARCH 1,1 Model (All figures are in ₹)							
Scenario Description	**90-%**	**95-%**	**98-%**	**99-%**	**STDEV**	**AVG**	**CV=stdev/avg**
Delhi Chennai							
AVG Non-Parametric	1078	1282	1532	1696	**272.31**	**1396.77**	**0.19**
AVG Parametric	3780	4494	5370	5946	**954.86**	**4897.78**	**0.19**
AVG Tailed	-6256	-7439	-8888	-9842	**1580.39**	**-8106.29**	**-0.19**
Mumbai Delhi							
AVG Non-Parametric	995	1183	1413	1565	**251.31**	**1289.06**	**0.19**
AVG Parametric	5539	6586	28331	8714	**10773.62**	**12292.57**	**0.88**
AVG Tailed	-3749	-4458	-5423	-5898	**964.10**	**-4881.78**	**-0.20**
Mumbai Chennai							
AVG Non-Parametric	76	90	108	119	**19.12**	**98.07**	**0.19**
AVG Parametric	151	180	215	238	**38.17**	**195.80**	**0.19**
AVG Tailed	-837	-995	-1189	-1316	**211.38**	**-1084.25**	**-0.19**

Table 2 . "191- Month Horizon Portfolio Risk Capital" Based on Traffic Signal Violations Approach with Generalized Autoregressive Heteroskedasticity Model (GARCH 1,1)

(1996-97 to 2011-2012)

Portfolio Risk Capital using GARCH 1,1 Model (All figures are in ₹)							
Scenario Description	**90-%**	**95-%**	**98-%**	**99-%**	**STDEV**	**AVG**	**CV=stdev/avg**
Delhi - Chennai							
Portfolio Risk Capital Non -Parametric	4201	4995	5968	6608	**1061.11**	**5442.78**	**0.19**
Portfolio Risk Capital Parametric	-13212	-15709	-18771	-20785	**3337.52**	**-17119.13**	**-0.19**
Portfolio Risk Capital Tailed	-24979	-29701	-35489	-39296	**6310.06**	**-32366.19**	**-0.19**
Mumbai - Delhi							
Portfolio Risk Capital Non-Parametric	3904	4642	5546	6142	**986.19**	**5058.48**	**0.19**
Portfolio Risk Capital Parametric	-4645	-5523	-6600	-7308	**1173.46**	**-6019.03**	**-0.19**
Portfolio Risk Capital Tailed	-14969	-17799	-21268	-23550	**3781.49**	**-19396.42**	**-0.19**
Mumbai - Chennai							
Portfolio Risk Capital Non-Parametric	242	288	344	381	**61.15**	**313.65**	**0.19**
Portfolio Risk Capital Parametric	-1939	-2306	-2755	-3051	**489.90**	**-2512.86**	**-0.19**
Portfolio Risk Capital Tailed	-3388	-4029	-4814	-5330	**855.94**	**-4390.35**	**-0.19**

framework of industries that are extremely affected by abnormal temperature variations. The use of random numbers, the use of historical simulation, and tailed concept as applied here in this paper can further be applied into other weather variables like humidity, rainfall, and so forth. The risk capital estimation using temperature data is perhaps an analysis of a new kind by adding a suitable multiple which can describe the relationship of temperature with the volume of sales. This study can directly provide the strategic financial modeling approach for safeguarding companies against poorly measured sales data due to abnormally high temperature movements.

Conclusion

In the long term, considering portfolios based on temperature values seems to be a relevant option as temperature volatilities are linked to utility prices and thus impact economies to a large extent. Not only this, agriculture based economic growth in India mainly demands a mechanism to monitor the financial institutions' preparedness by taking volatilities of such fundamental factors into account. Also, temperature patterns vary according to location and hence, micro level risk assessment of weather related investments is the order of the day. Much is needed in this direction from the Indian perspective. There is a possibility that prices of essential food grains, which are reflected in inflation, can be linked to how far we can gauge the performance of temperature and other weather patterns with predominately ARCH type analysis as revealed earlier.

Banks extending major credit to the agricultural industry must be allowed to manage their capital adequacy requirements on a geographical basis and thus, this will put lesser load on risk capital requirements. There is indeed a good scope to understand how stock markets and other financial and non-financial industries in India can adopt this model to maintain a balance between long term risk-return frameworks.

Limitations of the Study and Scope for Further Research

The present study is mainly confined to three cities of India, and within the time specified, another limitation is probably the time gap, that is, the monthly temperature variations, which is making this literature limited to understanding the monthly hedging possibilities only. While taking random values as a proxy to normally distributed data (for parametric estimation), the tailed component seems to be revolving around the random component as compared to the actual historical values of the temperature data.

Research studies in the future can cover more cities, more climatic variables other than temperature, humidity, rainfall, precipitation, and so forth. The use of EGARCH 1,1 and EGARCH (p,q) lag series can be implemented, which can cover the 'leveraging effect' in the volatility clustering more easily for these temperature data. Instead of the 2- asset portfolio combination, the multi-asset portfolio combination will provide more fruitful results and bring comprehensiveness in the study.

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